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Citation for published version:

Yin, Z, Feng, T & MacBeth, C 2019, 'Fast assimilation of frequently acquired 4D seismic data for reservoir history matching', *Computers and Geosciences*, vol. 128, pp. 30-40.
<https://doi.org/10.1016/j.cageo.2019.04.001>

Digital Object Identifier (DOI):

[10.1016/j.cageo.2019.04.001](https://doi.org/10.1016/j.cageo.2019.04.001)

Link:

[Link to publication record in Heriot-Watt Research Portal](#)

Document Version:

Peer reviewed version

Published In:

Computers and Geosciences

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Accepted Manuscript

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PII: S0098-3004(18)30895-1

DOI: <https://doi.org/10.1016/j.cageo.2019.04.001>

Reference: CAGEO 4256

To appear in: *Computers and Geosciences*

Received Date: 29 September 2018

Revised Date: 14 February 2019

Accepted Date: 2 April 2019

Please cite this article as: Yin, Z., Feng, T., MacBeth, C., Fast assimilation of frequently acquired 4D seismic data for reservoir history matching, *Computers and Geosciences* (2019), doi: <https://doi.org/10.1016/j.cageo.2019.04.001>.

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FAST ASSIMILATION OF FREQUENTLY ACQUIRED 4D SEISMIC DATA FOR RESERVOIR HISTORY MATCHING

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Keywords: Data assimilation; Morris sensitivity analysis; ES-MDA; Seismic history matching; Uncertainty reduction.

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1. Introduction

4D seismic monitoring is of significant importance for hydrocarbon reservoir surveillance and CO₂ sequestration assessment. For instance, 4D seismic data has shown the strongest impact on deep-water developments in West Africa and the Gulf of Mexico (Johnston, 2013). At Sleipner field, with support from the frequently acquired 4D seismic monitors, nearly 16 million tons of CO₂ has been stored to the reservoir (Xue et al., 2017). To quantitatively maximize the value of information captured by the 4D surveys, the 4D seismic data has to be assimilated to the reservoir prediction models. This data assimilation procedure is called seismic history matching (SHM), which closes the loop between the observed 4D seismic (and production) and that predicted by reservoir models (Gosselin, 2003; Stephen et al., 2006; Yin et al., 2017; Zhang & Leeuwenburgh, 2017). The objective is to quantitatively reduce the uncertainty surrounding reservoir management decisions, by obtaining reliable prediction of reservoir behaviours using history-matched reservoir models. It is believed that the 4D seismic adds spatial constraints to the reservoir simulation models, and thus helps to tackle the problem of non-uniqueness in the ill-posed conventional production history matching (HM).

Because of the valuable information provided by the 4D seismic, frequently repeated seismic monitoring has nowadays become more widely applied in offshore environments through the towed-streamer technology. Table 1 provides a snapshot of the fields that have five or more repeated 4D seismic surveys from the literatures. To enhance the data quality and obtain seismic monitors more frequently, seabed permanent reservoir monitoring (PRM) has become popular to provide life-of-field seismic surveys. Table 2 collects a number of the major fields throughout the world that have the PRM system installed. For these fields, the permanently installed acquisition system delivers well resolvable 4D seismic data within a rapid-turn-around processing time. For example, in Ekofisk, it enables excellent 4D seismic data to be obtained every six-months (Grandi et al., 2013). The most recent progress has come from the continuous seismic monitoring technique of “SeisMovie” (Mateeva et al., 2015). With a land buried

source and receiver arrays, this PRM system offers time-lapse seismic data that can image subtle reservoir changes on a daily basis. These frequently acquired surveys enable the 4D seismic data to impact the reservoir development decisions promptly regarding infill well drillings, well interventions and production optimization.

However, such frequent 4D seismic acquisition imposes new challenges to the conventional SHM workflows. First, history matching to multiple 4D seismic surveys requires the ability to handle large volumes of seismic data created by the high number of seismic surveys. It can be very computationally cost and time-consuming if using the traditional history matching workflow that attempts to match each individual time-lapse seismic. Besides, using 4D seismic directly as history matching input data without proper analysis may lead to seismic errors being propagated systematically to the quantitative SHM workflows (Alfonzo et al., 2017). This is because as an ill-posed inverse problem, SHM is sensitive to data errors which means small errors in data can result in large fluctuations in the prediction (Li, 2017). This problem can further propagate with the increased number of 4D seismic surveys.

In this paper, we propose a framework to efficiently assimilate the frequently acquired 4D seismic data in SHM. A new 4D seismic attribute (named “well2seis”) for history matching is firstly introduced that condenses the many repeated 4D seismic data into a single unitless attribute by correlating them to the reservoir production performances. This not only compresses the big volumes of frequently acquired 4D seismic into a single attribute for efficient assimilation, but also reduces the uncertainty of the 4D seismic observations by summarizing them based on production performances. Morris sensitivity analysis is adapted to investigate the uncertainty parameters in the reservoir model. Once the reservoir uncertainty parameters are confirmed, a well2seis objective function (OF) is constructed to quantify the misfit between the observed well2seis (calculated using observed 4D seismic and production data) and modelled well2seis (calculated using modelled 4D seismic and production performances). In the conventional SHM, because production and seismic data are in different metrics (Chassagne et al., 2016), the weights on seismic and production misfits have to be properly specified when combining them into the OF. But this

is avoided when using well2seis OF, as it uses only the well2seis to calculate the misfit, while summarizing information from both 4D seismic and production data. ES-MDA is applied at the end to minimize the well2seis OF by calibrating the uncertainty model parameters identified by the Morris sensitivity analysis. This proposed workflow is tested on a North Sea field reservoir and compared to the conventional production and seismic history matching practices.

2. Data assimilation framework for frequently acquired 4D seismic data

2.1 Condensing the frequently repeated 4D seismic data

All the reservoir-induced dynamic changes detected by 4D seismic data are caused by fluid extraction or injection activity from the wells. 4D seismic signals therefore cannot be unambiguously interpreted without a clear understanding of the field production and injection behaviours. Considering a reservoir with n repeated time-lapse seismic surveys acquired during the development, a total of $N=n*(n-1)/2$ 4D seismic differences can be generated for all paired combinations of surveys. They will construct a 4D seismic sequence vector:

$$\Delta A(x, y, z) = [\Delta A_{t1}(x, y, z), \Delta A_{t2}(x, y, z), \dots, \Delta A_{ti}(x, y, z), \dots, \Delta A_{tN}(x, y, z)]$$

Eq. 1

where $\Delta A_{ti}(x, y, z)$ represents the 4D seismic attribute such as amplitude or impedance (in 2D map or 3D volume) changes at each reservoir location (x, y, z) at 4D acquisition time interval ti . The reservoir fluid (extraction or injection) changes during the corresponding 4D acquisition time intervals can be derived by the combination of observed production and injection data weighted by formation volume factors, or the reservoir pressure variations can be measured from wells (e.g. bottom-hole pressure (BHP) measurements). This type of well behaviour data constitutes another time sequence vector:

$$\Delta V = [\Delta V_{t1}, \Delta V_{t2}, \dots, \Delta V_{ti}, \dots, \Delta V_{tN}]$$

Eq. 2

For non-compacting sandstone reservoirs, Huang and MacBeth (2012) and Yin et al. (2015) proved that the 4D seismic sequence $\Delta A(x, y, z)$ can be linearly correlated to the well behaviour sequence ΔV . Putting the 4D seismic and well behaviour time sequences together, a normalized cross-correlation factor $W2S$ (named as the “well2seis attribute”) can be obtained for any location (x, y, z) of the reservoir:

$$W2S(x, y, z) = \frac{cov[\Delta A(x, y, z), \Delta V]}{\sqrt{var[\Delta A(x, y, z)] \times var(\Delta V)}}$$

Eq. 3

The metric $W2S(x, y, z)$ ranges from 0 for no correlation (which means the well behaviour is not responsible for the 4D seismic change), to ± 1 for a perfect correlation. Either -1 or +1 can be a perfect correlation, depending on the polarity of seismic attributes. The measure of correlation quantifies how the well injection and production activities are responsible for 4D seismic signatures at a specific point. Once the $W2S$ has been calculated for every location within the reservoir, the distribution of this attribute (either as 2D map or 3D cube) will reflect the connection between the 4D seismic signals and the well behaviour, which implicitly measures the degree of reservoir spatial connectivity to the wells of interest. As the well2seis attribute condenses all the 4D seismic data from multiple surveys and well performance information, in principle, the history matching of $W2S(x, y, z)$ solely should improve the match to each individual 4D seismic set as well as the production observations. This further helps to avoid the problem in the traditional SHM workflows where proper weights on the input 4D seismic and production data respectively are required when designing the misfit objective function.

Before assimilating the observed well2seis to history match reservoir models, the measurement error c^{w2s} contained in the well2seis observations has to be properly quantified. Here, we consider that the observed well2seis $W2S^{obs}$ contains the true value $W2S^{true}$ and observation error c^{w2s} .

$$W2S^{obs} = W2S^{true} + c^{w2s}$$

92 Eq. 4

93 Eq. 3 suggests that the well2seis observation error c^{w2s} comes from its input data – 4D seismic and
 94 production observations. The observed 4D seismic attribute ΔA^{obs} contains both true signal ΔA^{true} and
 95 noise c^{seis} .

$$\Delta A^{obs} = \Delta A^{true} + c^{seis}$$

96
 97 Eq. 5

98 The 4D seismic noise to signal ratio (NSR) can be calculated (Behrens et al., 2002):

$$NSR = \frac{NRMS}{\sqrt{2 - NRMS^2}}$$

99 Eq. 6

100 where NRMS is the 4D seismic non-repeatability (Kragh & Christie, 2002)

$$NRMS = 2 * \frac{RMS(A_{t1} - A_{t2})}{RMS(A_{t1}) + RMS(A_{t2})}$$

101 Eq. 7

102 where A_{t1} and A_{t2} are 4D seismic surveys shot at different times, and RMS represents the root mean
 103 square. The 4D seismic noise c^{seis} is therefore obtained:

$$c^{seis} = \Delta A^{obs} \times \frac{NSR}{1 + NSR}$$

104 Eq. 8

105 Similarly, the production observations ΔV^{obs} can also be written as

$$\Delta V^{obs} = \Delta V^{true} + c^{prod}$$

106 Eq. 9

c^{prod} is commonly regarded as Gaussian distributed observation errors of production data, and can be provided by field engineers.

Based on the well2seis error computation equations derived in Yin et al. (2015), the well2seis observation error can be calculated as

$$\begin{aligned} c^{w2s} &= 1 - \sqrt{1 - \frac{var(c^{seis})}{var(\Delta A^{obs})} - \frac{var(c^{prod})}{var(\Delta V^{obs})} + \frac{var(c^{seis})}{var(\Delta A^{obs})} \times \frac{var(c^{prod})}{var(\Delta V^{obs})}} \\ &= 1 - \sqrt{1 - a - b + a \times b} \end{aligned}$$

Eq. 10

Here, the term a represents the noise level from the observed 4D seismic attribute. According to Behrens et al. (2002), the 4D seismic noise level should be below 25% for quantitative use of the 4D data. For the term b which is the error from production observations, it is normally in much smaller scale than the 4D seismic noise, and here we assume it's below 10%. Eq. 10 is then plotted in Figure 1, which shows the distribution of c^{w2s} against the 4D seismic noise and production observation error. As indicated by the figure, well2seis correlation error should be mostly within twenty percent (marked by the dashed yellow box). This suggests that because of the constraint from the relatively low uncertainty production data, the well2seis helps to reduce the noise levels in 4D seismic, which is an important concern for the quantitative use of 4D seismic data.

2.2 Morris sensitivity analysis

The second step designs sensitivity analysis (SA) to investigate how the variation of reservoir model parameters can impact the response of the well2seis attribute $W2S(x, y, z)$. This is an essential step to determine the model parameters that can be updated by the well2seis. For oil and gas reservoir studies, one popular SA method is called one-at-a-time (OAT) approach (Daniel, 1973), and it is commonly used due to its simplicity. The OAT method varies the model input parameters m one by one, while keeping

the rest parameters fixed at each test. Each parameter is tested under its extreme high and low conditions, and then the corresponding model response changes from its reference case are monitored. The OAT sensitivity analysis therefore requires at least $2N_p + 1$ number of model tests, where N_p is the number of parameters. However, the OAT only measures the linear effects of each individual parameters, while nonlinear effects (or interaction effects) are not considered.

The Morris SA (Morris, 1991) method further develops the concept of OAT by strictly designing the experiment trajectories through model parameter variable space. This helps it to avoid the limitations of the standard OAT to be a reliable SA technique for identifying influential parameters for models with large amount of uncertainty parameters (Herman et al., 2013; King & Perera, 2013; Scheidt et al., 2018). In Morris Method, each parameter is first scaled to the unit interval $[0,1]$, and discretized to q intervals $[0, \frac{1}{q-1}, \frac{2}{q-1}, \dots, 1]$, resulting the experiment space Ω . The experimental step, Δ , is the parameter base value multiplied by $\frac{1}{q-1}$. Similarly to the standard OAT, the elementary effect (EE_i) of the i -th parameter m_i can be calculated by perturbing the i -th parameter of a base (or starting) point $\mathbf{m} = (m_1, \dots, m_i, \dots, m_{N_p}) \in \Omega$: add the experimental increment Δ to the parameter while keeping the rest parameters unchanged.

$$EE_i = \frac{f(m_1, m_2, \dots, m_i + \Delta, \dots, m_{N_p}) - f(m_1, m_2, \dots, m_i, \dots, m_{N_p})}{\Delta}$$

Eq. 11

where $f(\cdot)$ is the well2seis forward modelling. For each starting point $\mathbf{m} \in \Omega$, N_p perturbations tests to evaluate the elementary effects of the N_p model parameters, and this constructs one trajectory. By randomly sampling the starting points from Ω , multiple trajectories are created to estimate the distribution of elementary effects for each parameter. As each trajectory is a OAT design, for a Morris SA that has L trajectories, $L(N_p + 1)$ model evaluations are required. Once all the elementary effects are obtained for

each parameters in each trajectory, the sensitivity μ_i of each parameter m_i can be calculated as the mean of its elementary distribution, and its interaction effects with other parameters is calculated as the standard deviation σ_i .

$$\mu_i = \frac{1}{L} \sum_{l=1}^L EE_i^l \text{ and } \sigma = \sqrt{\frac{1}{L-1} \sum_{l=1}^L (EE_i^l - \mu_i)^2}$$

Eq. 12

The mean μ_i quantifies the overall impact of the parameter m_i on the well2seis response. A large μ_i in contrast to the other parameters indicates that the well2seis response is highly sensitive the model parameter m_i . The standard deviation σ_i is a measurement of the interaction effects of m_i . A large value of σ_i suggests that parameter becomes more influential when interacting with other parameter variables that results a high non-linear effect on the well2seis output.

The Morris SA has proved to be effective and reliable from its wide application in various domains such as ecosystem models (Morris et al., 2014), environmental modelling (Campolongo et al., 2007), flood inundation models (Pappenberger et al., 2008), and hydrological studies (Dessirier et al., 2015; Herman et al., 2013; King & Perera, 2013). But it is only recent that this method draws the attention from the oil/gas reservoir modelling studies, and hasn't been sufficiently used for data assimilations apart from very few applications (Gervais-Couplet et al., 2010; Scheidt et al., 2018). In this paper, we applied the Morris method to screen the model uncertainty parameters for the well2seis data assimilation.

2.3 History matching of the well2seis observations

Here, the $W2S$ objective function (OF) is defined to measure the misfit between observed and modelled well2seis attributes

$$OF = (W2S^{obs} - W2S^{sim})^T C_D^{-1} (W2S^{obs} - W2S^{sim}) + (m - m_{prior})^T C_m^{-1} (m - m_{prior})$$

Eq. 13

where $\mathbf{W2S}^{obs}$ and $\mathbf{W2S}^{sim}$ are respectively the vectors of observed and simulated well2seis correlations of the reservoir, \mathbf{C}_D^{-1} is the inverse of the covariance matrix of well2seis observation error c^{w2s} , \mathbf{m} is a vector that contains the uncertain parameters in the model which should be updated during history matching, \mathbf{m}_{prior} is the vector of uncertain parameters in the prior models, and \mathbf{C}_m^{-1} is the inverse of the prior covariance matrix of model parameters.

Once the uncertainty parameters of the reservoir model are confirmed from the Morris SA, an Ensemble Smoother with Multiple Data Assimilation (ES-MDA) will be employed to assimilate the observed well2seis to calibrate the uncertainty parameters by minimizing the $W2S$ OF. Initially proposed by Emerick and Reynolds (2012), the ES-MDA is extended from the Ensemble Smoother (ES) data assimilation method (Skjervheim & Evensen, 2011; van Leeuwen & Evensen, 1996), while the ES was developed from the well-known Ensemble Kalman Filter (EnKF) that have been widely used to solve history matching problems since its first introduction by Evensen (1994). But the ES-MDA outperforms the EnKF and ES by providing better data matches according to various studies (Emerick & Reynolds, 2012;2013). The basic mathematical form of the ES which extended from EnKF is:

$$\mathbf{m}_j^a = \mathbf{m}_j^f + \mathbf{C}_{MD}^f (\mathbf{C}_{DD}^f + \mathbf{C}_D)^{-1} (\mathbf{d}_{obs} - \mathbf{d}_j^f)$$

Eq. 14

where \mathbf{m} is the vector that contains the model parameter (e.g. permeability, porosity) vector. The subscript j denotes the index of the ensemble member, and superscript a represents the updated forecast results, while f is the initial model simulated result. The term \mathbf{C}_{MD}^f is the cross-covariance matrix between the prior model parameters vector and predicted data vector, while \mathbf{C}_{DD}^f is the covariance matrix of the predicted data, and \mathbf{C}_D is the measurement error covariance of observation data. \mathbf{d}_{obs} stands for the vector of observation data (which is the observed $W2S$), while \mathbf{d}_j^f is corresponding predicted data (simulated

W2S) from the model j . The limitation of ES is that it is designed to solve linear problems, while most of the history matching problems (especially for 4D seismic) are nonlinear. Besides, the above ES equation only runs a single global update, the data assimilation may finish without reaching acceptable matching results. ES-MDA solves these problems by iteratively re-running the ES by inflating the measurement error covariance matrix until the assigned iteration number N_a is reached. From the study of Emerick (2016 & 2018), ES-MDA has shown great potentials for the effective assimilation of seismic data. Here, the ES-MDA is setup using the following three steps initially proposed by Emerick and Reynold (2012):

1. Choose the number of data assimilation iterations, N_a , and the covariance inflation coefficients α_i for each iteration i of $1, 2, \dots, N_a$.
2. Generate the initial ensemble experiment models $\{\mathbf{m}_j^{f,0}\}_{j=1}^{N_e}$ for $i = 0$, where N_e is the total number of reservoir models in the ensemble.
3. For i from 1 to N_a :
 - 1) Run the ensemble reservoir models from time zero.
 - 2) For each ensemble member, generate an observation vector (the observed well2seis) perturbing with the inflated measurement error (here is the well2seis error calculated by Eq. 10): $\mathbf{d}_{uc,j}^i \sim N(\mathbf{d}_{obs}, \alpha_i \mathbf{C}_D)$.
 - 3) Update the ensemble models by adjusting the equation Eq. 14:

$$\mathbf{m}_j^{a,i} = \mathbf{m}_j^{f,i} + \mathbf{C}_{MD}^{f,i} (\mathbf{C}_{DD}^{f,i} + \alpha_i \mathbf{C}_D)^{-1} (\mathbf{d}_{uc,j}^i - \mathbf{d}_j^{f,i})$$

$$\mathbf{m}_j^{f,i} = \mathbf{m}_j^{a,i-1}$$

Eq. 15

As can be seen from the Eq. 15 of the Step 3, the ES-MDA enables iterative assimilations of the well2seis observations to the reservoir models. Furthermore, as an ensemble-based methods, the ES-MDA will also

provide an ensemble of reasonable estimates of the model uncertainties for scenario analysis and risk management.

3. Field case application

3.1 A North Sea reservoir case

To demonstrate the application of the above proposed data assimilation workflow, we applied it to a reservoir model derived from a real North Sea field with frequently repeated 4D seismic acquisitions. With the geological features and development history kept unchanged as the real field, this reservoir model is generalized to be a prototype reservoir case to investigate the data assimilation problems of history matching. We create a “Truth” case by picking a best history matched reservoir model to generate all the data and predictions (hence we “know” the actual future). Figure 2(a) shows the initial fluid distribution of the “Truth” reservoir, where three production wells (P1, P2 and P3) are drilled in the upper flank, and there are two water injectors (I1 and I2) in the lower flank of the reservoir. The production of the field has been driven predominantly by injected water flooding since the first oil in 1995. Same as the real field, it is found that pressure and water cut of the synthetic reservoir are quite challenging to be history matched to the observed data, unless the reservoir uncertainty is properly understood. In the Base case reservoir model, both the static parameters (e.g. porosity, permeability, faults) and dynamic parameters (e.g. fluid relative permeability) are uncertain. Figure 2(b) shows the observed (“Truth” case) and initial simulation model predicted bottom-hole pressure (BHP) and production water cut performances from the producers. We use the observed 4D seismic and production data before 2008 (the latest 4D survey) for history matching, while the observation data from 2008 to 2012 is used as prediction to examine the history matching performance.

The major modelling uncertainties of this North Sea field come from fault connectivity, porosity, permeabilities, connectivity of an intra-reservoir shale layer (stratigraphic barrier), and oil-water relative permeabilities. As shown from Figure 3(a), there is one main structural fault (EF) that divides the reservoir into two compartments, while this fault consists of two segments: EF_south in the lower flank

and EF_north in the upper flank. Figure 3(b) and (c) show the spatial distribution of reservoir porosity and permeability in the reservoir model. There is a thin intra-reservoir shale layer which separates the reservoir connection vertically, as illustrated in Figure 3(d). Proper understanding of its connectivity is crucial to reliable prediction of the reservoir production, but this is very challenging due to the limitation of seismic data resolutions. The relative permeabilities of oil and water fluid phases are uncertain as laboratory measurements for this sector are not available. The initial estimate of the relative permeability for oil (K_{ro}) and water (K_{rw}) varies within a range as illustrated in Figure 3(e).

3.2 Multiple 4D seismic surveys and well2seis application

A total of six repeated time-lapse seismic surveys were acquired on the field with the first survey (S1) obtained in 1991, and five subsequent seismic monitors shot in 1998 (S2), 2001(S3), 2004(S4), 2006(S5) and 2008(S6) during the field development, as shown in Figure 2(b). The observed 4D seismic surveys are shot on the “Truth” case using simulator-to-seismic modelling (Amini, 2014). The six seismic surveys can provide totally fifteen 4D seismic differences, which contain the reservoir dynamic information at fifteen different 4D time intervals. Figure 4 shows the mapped 4D seismic amplitude differences generated from the observed 4D seismic surveys, which will constitute the observed 4D seismic sequences of the Eq. 1. Initially, it is observed that the 4D seismic mainly captures the hardening 4D seismic signals of water flooding (seismic amplitude increase, coloured as blue in the maps of Figure 4) in the upper flank near the producers. In the down flank area, the hardening effect caused by water flooding and the pressure increase induced softening effect (amplitude increase, coloured as red in the maps) cancel each other out. This means the softening 4D seismic responses are only observed around the injectors with the highest pressure changes, and the hardening signals are dominant. Besides, the maps of $\Delta A1$ and $\Delta A3$ in the Figure 4 show clear contrast of hardening effects across the fault EF_south, suggesting the water flooding may be blocked by this fault segments, which is consistent with the fault sealing property in the “True” field case. All these are important information that needs to be assimilated to the reservoir model.

To make efficient use of all the 4D seismic data, all the fifteen 4D seismic maps are correlated to the production data to generate well2seis attribute using Eq. 3. First, the total six 4D seismic surveys were correlated to the twelve-year's cumulative oil production combined from all the producers. As the results shown in Figure 5(a), the distribution of the high W2S attribute values clearly outlines the flow path of the injected water. It reveals that the water injection from I1 and I2 bypassed the fault barrier, traversed the open fault segment and then reached the producers P1 and P2 in the left reservoir compartment. The sealing effect of the fault barrier is clearly identified by the distinct contrast of the W2S distributions across the fault, and the conduits are correctly located by the continuous W2S distribution. Compared to the original 4D seismic difference in Figure 4, the signal is much further enhanced, especially in the lower flank area, such that the effect of the fault barrier becomes very evident. Figure 5(b) is the well2seis map obtained by correlating the average BHP history from all the wells to the 4D seismic. On this map, the distribution of the high correlation values delineates the areas where the pressure responses vary consistently with the well performances. Compared to the original 4D seismic maps (Figure 4) where the pressure seismic signals are generally weak and are masked by the effect water flooding effects, we can clearly observe that the pressure signals are significantly enhanced by well2seis, especially in the lower flank area near the fault EF_south and the injectors.

3.3 Prior model uncertainty and Morris sensitivity analysis

The initial uncertainty of the prior reservoir models is estimated through the discussion with the geologists, geomodellers and reservoir engineers who operate the real field. The uncertainty of the reservoir model is divided into grid-independent and grid-dependent components. The grid-independent components are the relative permeabilities of the reservoir fluids (oil and water). We employ the Brooks-Corey model (Brooks & Corey, 1964) to parameterize the water and oil relative permeabilities, and uncertainty of the relative permeabilities are controlled by the Corey coefficients for water (NW) and oil (NO) respectively. The grid-dependent components are transmissibility of the fault EF_south and EF_north, horizontal permeability (Kh), Kv/Kh ratio, porosity, and transmissibility across the shale layers.

To simplify the process of the parametrization, we deal with those gridded uncertainty components by assigning multipliers separately. Table 3 summarizes the total eight uncertainty parameters, with the prior estimation of their uncertainty probability distribution function (*PDF*).

Once the uncertainty parameter variables are defined, two sets of Morris SA experiments are performed to evaluate parameters' sensitivity to the water-flooding and pressure well2seis attributes respectively. Each experiment is conducted by constructing a 20 trajectories and 6 levels ($p = 6$) Morris design. For this reservoir case with eight variables, 20 trajectories are supposed to be sufficient to ensure the convergence of the Morris sensitivity results, while 6 levels can provide appropriate sampling range for the parameter variable perturbations. The calculated Morris sensitivity μ_i and interactive effects σ_i indices of each parameter m_i are shown in the radar plot in Figure 6. In the results, the non-zero sensitivity μ (the black circle plotted results in the figure) suggests that the model parameters perform differently to the two types of well2seis attribute. For the water-flooding well2seis, it shows that Porosity, Kh, K_{rw} are mostly sensitive, with K_{ro}, EF_{south} and Stratigraphic barrier relatively sensitive, while EF_{north} and K_v/Kh are almost non-sensitive. However, for the other experiment on the BHP (pressure) related well2seis, K_v/Kh, K_{ro}, K_{rw}, EF_{south} and EF_{north} become significantly sensitive. Besides, parameters with high μ are supposed to have significant interactive effects σ with other parameters (the red-cross plot). In brief, the Morris SA indicates that all the eight uncertainty parameters are sensitive to the well2seis attribute.

3.4 ES-MDA data assimilation and results

Using the above defined prior uncertainty *PDF*, Monte Carlo experiments are performed to generate 100 samples to construct the prior ensemble models. The left column of Figure 7 presents the distribution of each parameters of the 100 initial ensemble models. The simulated reservoir production performances from the prior ensembles are shown by the blue curves in Figure 8, while the observed produced history is plotted as black dots with observation error bar. The same simulator-to-seismic modelling approach developed by Amini (2011) are applied to the prior models to generate the simulated 4D seismic, with all

the input settings same as the “Truth” case. Figure 9(b) shows the ensemble mean of the simulated 4D seismic responses from 1995 to 2008, with the observed 4D seismic displayed in Figure 9(a). By comparing the simulated production performances and 4D seismic responses to the observations, the mismatch caused due to the large parameter uncertainty can be clearly identified.

The ES-MDA is then performed by taking both the water-flooding and pressure well2seis observations as the observation data. We assigned 15% white noise to observed 4D seismic data, while production observation error (Gaussian Distributed) is supposed to be within 10% according to the reservoir production engineers. This provides 11.97% observations errors in the well2seis based on the calculation from Eq. 10 to construct the covariance of well2seis measurement errors. When running the ES-MDA, a total of three data assimilation iterations are performed by setting the inflation factors as $\alpha_1 = \alpha_2 = \alpha_3 = 3$.

The histogram plots in the right column of Figure 7 present the posterior *PDF* of the model parameters after the third ES-MDA iteration, with the “True” case value marked by the red arrows. It shows that the posterior *PDF* significantly converges towards the truth values. The posterior model simulation results of production performances are shown in Figure 8, where the green curves are from the second iteration and the orange curves are from the third iteration. We can observe remarkable improvement of the production history matching quality. More importantly, by history matching to the historical data before the year of 2008, the prediction uncertainties are significantly reduced for next four years (2008-2012). Figure 9(c) shows the posterior ensemble mean of simulated 4D seismic difference between the latest survey S6 (2008) and the baseline survey S1 (1995). The improvement from the prior 4D seismic responses in Figure 9(b) is obvious, as the posterior result becomes almost the same as the observed 4D responses from the “True” case. The results suggest that by the assimilating the observed well2seis attributes to the reservoir models, the ES-MDA effectively reduces the uncertainty of model parameters after two iterations, resulting in large improvements of the production and 4D seismic matching quality. The third

iteration further reduces the prediction uncertainties that almost results in ensemble collapse. This suggests the well2seis can be very sensitive to the uncertainty parameters. The production performance predictions become more reliable by matching the historical data, hence enabling posterior models to be used for the reservoir development decision makings and managements.

4. Discussions

Our study further develops a cross-disciplinary dimensionless attribute uniting the frequently repeated 4D seismic surveys with the production data to calibrate reservoir models and reduce prediction uncertainty. This well2seis attribute for data assimilation first condenses all the available 4D seismic from multiple surveys into a single attribute, such that it avoids directly history matching to large volumes of seismic data created from the many repeated surveys. This improves the previous history matching practice on frequently repeated 4D seismic surveys that only selects certain number (2 or 3) of the multiple 4D seismic surveys for data assimilation (Alerini et al., 2014; Geng et al., 2017; Tolstukhin et al., 2014) while the dismissed seismic surveys which may contain important information of the reservoir. By conditioning the 4D seismic data which are normally of high noise level to the production data that has low uncertainty, the well2seis creates spatial attributes with lower uncertainties than the original 4D seismic observations.

4.1 Comparison to production and seismic history matchings

For comparison, the conventional production and seismic history matchings are applied separately by assimilating the production data and 4D seismic data respectively of the above field case. Figure 10(a) shows the history matching results to the production performances when only assimilating the production historical data from 1995-2008. Five ES-MDA iterations were run to reach a reasonably convergent prediction results (the cyan coloured curves in Figure 10(a)) when history matching to the production data only, while the data assimilation of well2seis achieves robust prediction results by only three iterations. This is because the production history matching only assimilates the spatially sparse data at the well

locations. This increases the data assimilation efficiency by nearly 2/5 by reducing the two time consuming iterations in reservoir data assimilation. In Figure 11(b), the simulated 4D seismic difference between S6 and S1 is also generated from the posterior models (fifth iteration) of the production data assimilation. Compared to the observed 4D seismic, the distinct mismatch shows that the history matching only to the production data can result poor matching to the 4D seismic data even when the production data is highly matched. Figure 10(b) and Figure 11(c) is the matching results to observed production and 4D seismic respectively when assimilating the 4D seismic data only. We can observe that the prediction of production performance is biased from the observations after the fifth iteration when assimilating the 4D seismic data only, even when the 4D seismic data is matched (Figure 11(c)).

4.2 Limitations

However the successful application of the well2seis data assimilation also depends on correct uncertainty specification of the prior models, as the ES-MDA updates the uncertain model parameters within their initial *PDF*. Inconsistent prior estimation may result the posterior model parameter collapses at its prior maximum or minimum while the predictions are still not correct. To avoid this, the Morris SA is recommended to firstly identify the sensitive model parameters by including all the possible uncertainty parameters into the sensitivity analysis. Then the estimated *PDF* of the uncertainty parameters should ensure that the prior can predict the observation data, otherwise it should be falsified, and the prior *PDF* should be re-specified. In the case study, the spatial distribution of porosity and permeability are kept unchanged. This is because they are derived from the field seismic interpretations and well-log data, and have already matched to observed 3D seismic according to seismic modelling. However, it would be more convincing to include the spatial heterogeneity to the history matching procedure, as the well2seis contains more spatial information.

Another challenge comes from the limited number of 4D seismic surveys, as this directly impacts the statistical significance of the well2seis attribute. According our empirical study on fields from the North Sea (Huang & MacBeth, 2012; Huang et al., 2011; Yin et al., 2015; Yin & MacBeth, 2014; Yin et al.,

2016), a minimum of four repeated seismic surveys are required in order to obtain statistically significant well2seis attribute. For cases with the minimum four surveys, Null hypothesis test (with the typical p-value of 0.05) shows the well2seis value need to be above 0.729 to be considered as statistically significant. This critical value decreases with the increase of seismic surveys. More details of the impacts of survey numbers on the well2seis statistical significance have been investigated by Yin (2016).

5. Conclusions

This paper presents a new scheme for fast assimilating of frequently repeated 4D seismic surveys that normally contains large volume of measurement data. Instead of using the conventional data assimilation methods that directly history match to the reservoir production history and 4D seismic data, the 4D seismic and production data are first correlated to generate a dimensionless cross-disciplinary attribute, which compresses the information from both the production history and many repeated 4D seismic surveys. This enables the data assimilating workflow to handle large volumes of the 4D seismic data, hence enhances the efficiency. Morris sensitivity analysis is introduced as a robust tool for oil and gas reservoir model uncertainty diagnosis to replace the traditional one-at-a-time sensitivity analysis method. The Morris SA suggests that the reservoir uncertainty parameters are sensitive to the proposed well2seis correlations, hence the observed well2seis attributes can be assimilated to calibrate reservoir models. ESMDA, an ensemble based iterative data assimilation algorithm, is then applied to assimilate the spatial well2seis attributes to calibrate the reservoir models. The application to a North Sea field derived case shows that by assimilating the observed well2seis to the simulation model, both the production history and 4D seismic observations are highly matched, and model prediction uncertainty are significantly reduced. Furthermore, the data assimilation also speeds up with the required history matching iterations (the most time-consuming step) reduced from five to three when compared to the traditional production and 4D seismic data history matching approaches.

6. Tables

Table 1. Examples of the fields with five or more than five successively repeated streamer 4D seismic surveys.

Field	Location	Operator	4D seismic surveys	References
Dalia	Offshore Angola	Total	Baseline, 2008, 2010, 2011, 2013, 2014	(Pluchery et al., 2013)
Gullfaks	North Sea	Equinor	1985, 1996, 1999, 2003, 2005, 2008, 2011, 2014	(Ayzenberg & Yin, 2016)
Gryphon	North Sea	Maersk	1990, 2000, 2002, 2005, 2011	(Mitchell et al., 2016)
Harding	North Sea	TAQA	1990, 2000, 2002, 2005, 2011	(Mitchell et al., 2016)
Heidrun	Norwegian Sea	Equinor	1991, 2001, 2004, 2006, 2008, 2011	(Yin & MacBeth, 2014)
Norne	Norwegian Sea	Equinor	1992, 2001, 2004, 2006, 2008, 2010	(Huang et al., 2013)
Foinaven, Schiehallion, Loyal fields	UKCS (west of Shetlands)	BP	1993/1996 (BL), 1999, 2000, 2002, 2004, 2006, 2008, 2010, 2013	(Campbell et al., 2015)
Sleipner	North Sea	Equinor	1994, 1999, 2001, 2004, 2006, 2008, 2010, 2012	(Xue et al., 2017)

Table 2. Fields with seabed PRM systems installed in the North Sea, offshore Brazil and Caspian Sea (data obtained from Caldwell et al. (2015); Eriksrud (2014); WGP (2014)).

Field	Location	Operator	Installation	Seismic Cable	Sensor coverage	Water depth
Valhall	North Sea	BP	2003	120 km	45 km ²	70 m
Clair	North Sea	BP	2006	45 km	11 km ²	140 m
ACG field	Caspian Sea	BP	2007/2010	492/552 km	-	400 m
Ekofisk	North Sea	ConocoPhillips	2010	200 km	60 km ²	75 m
Jubarte	Offshore Brazil	Petrobras	2012	36 km	9 km ²	1250 m
BC-10	Offshore Brazil	Shell	2013	95 km	36 km ²	1650 m
Snorre	Norwegian Sea	Statoil	2013-2014	480 km	190 km ²	325 m
Grane	Norwegian Sea	Statoil	2014	180 km	50 km ²	130 m

Table 3. Overview of the uncertainty parameters, and their uncertainty distributions in the prior ensemble models.

Parameter variables (m_i)	Description	Distribution type	Distribution range (min, max)
NW (Krw)	Corey Coefficient of water relative permeability	Uniform	(0, 6)
NO (Kro)	Corey Coefficient of oil relative permeability	Uniform	(1, 5)
EF_south	Fault transmissibility multiplier	Log Uniform	(10^{-5} , 10^0)
EF_north	Fault transmissibility multiplier	Log Uniform	(10^{-5} , 10^0)
Kh	Horizontal permeability multiplier	Uniform	(0.5, 1.5)
Kv/Kh	Vertical/horizontal permeability ratio	Uniform	(0.1, 0.7)
Porosity	Porosity multiplier	Uniform	(0.7, 1.3)
Stratigraphic barrier	Transmissibility multiplier of the intra-reservoir shale	Uniform	(0, 0.80)

7. Figures

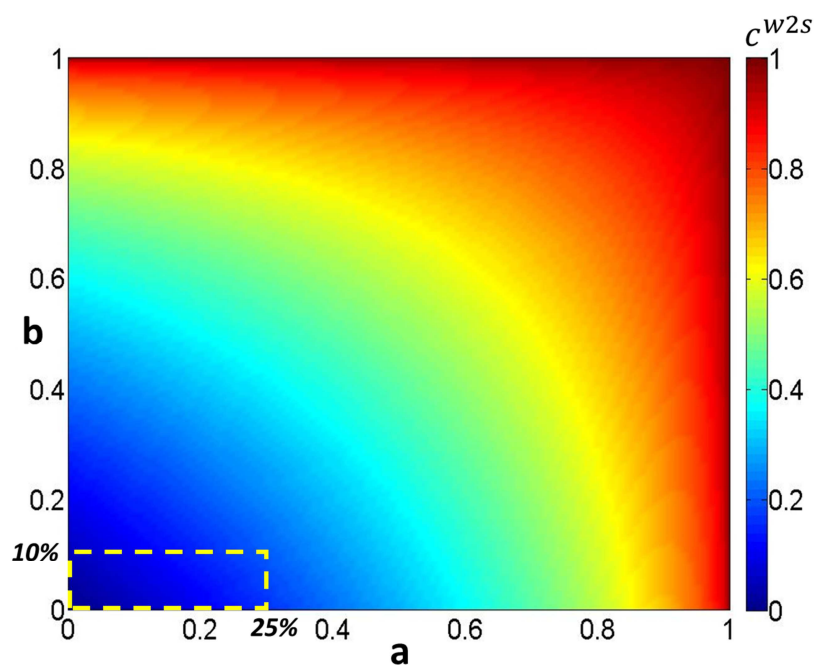


Figure 1. Plot of the equation Eq. 10 to quantify the distribution of the well2seis uncertainty c^{w2s} against the term a and b . The dashed yellow box marked area are the expected correlation errors for quantitative application ($a \leq 25\%$ and $b \leq 10\%$).

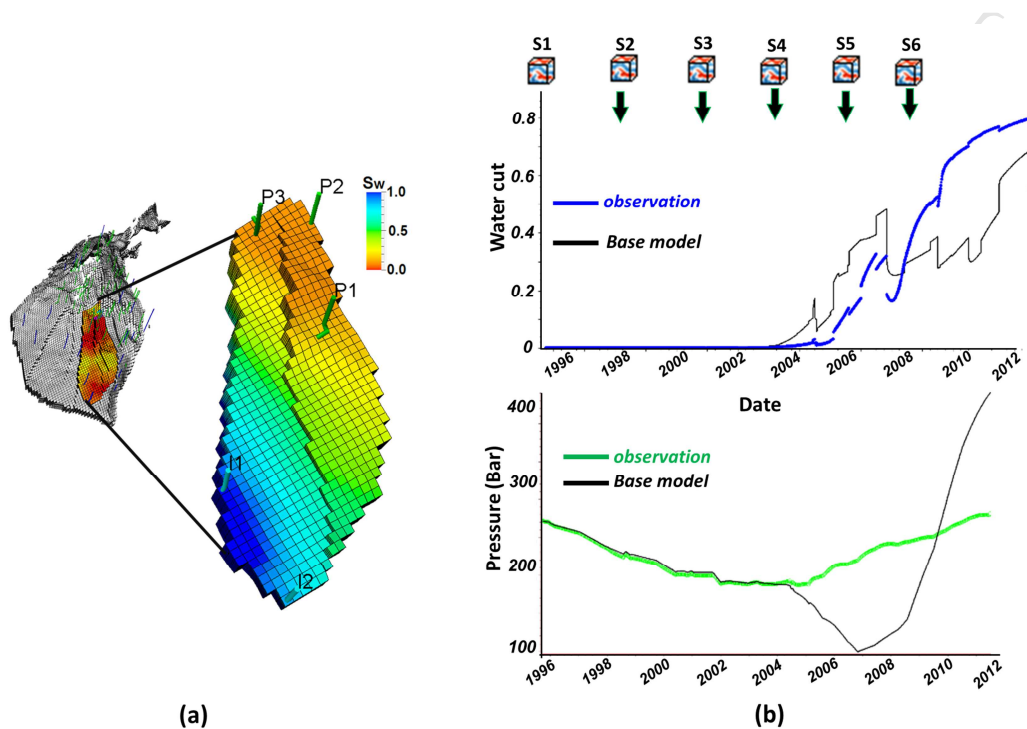


Figure 2. (a) Water saturation distribution and active wells of the North Sea field derived prototype reservoir. (b) Observed and simulated well performances – top: field production water cut; bottom: average BHP of the three producers. On the top of (b) shows the timing of the six 4D seismic surveys S1, S2, S3, S4, S5, and S6.

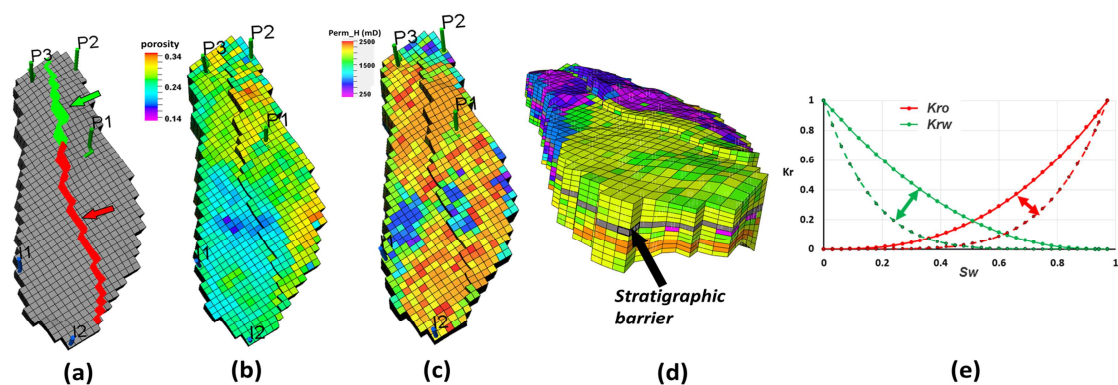


Figure 3. Visualization of the uncertainty reservoir model parameters: (a) Fault EF, where the green fault indicates the north segment (EF_north), while the red line indicate south segment (EF_south). (b) Reservoir porosity distribution. (c) Reservoir horizontal permeability distribution. (d) The intra-reservoir shale layer (“Stratigraphic barrier”) indicated by gray layer of the reservoir model. (e) The initial estimation of K_{ro} and K_{rw} uncertainty range.

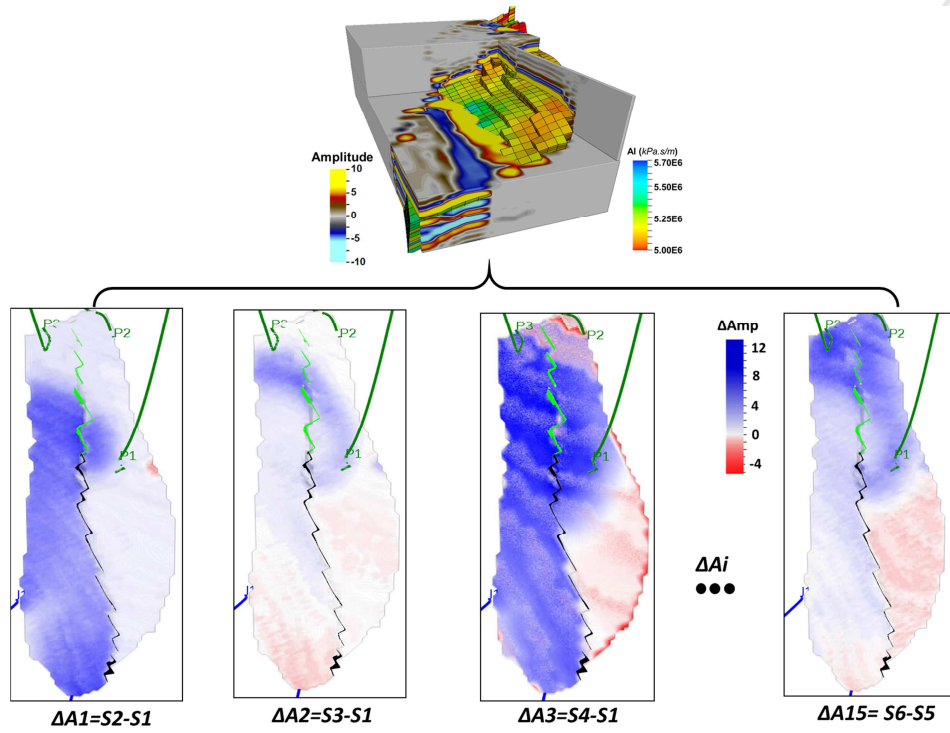


Figure 4. The observed 4D seismic attributes generated from all the paired combination of six seismic surveys. They construct the observed 4D seismic sequence $[\Delta A_1, \Delta A_2, \dots, \Delta A_{15}]$ of Eq1. The seismic surveys for the true model are acquired using seismic modelling approach from (Amini, 2014)).

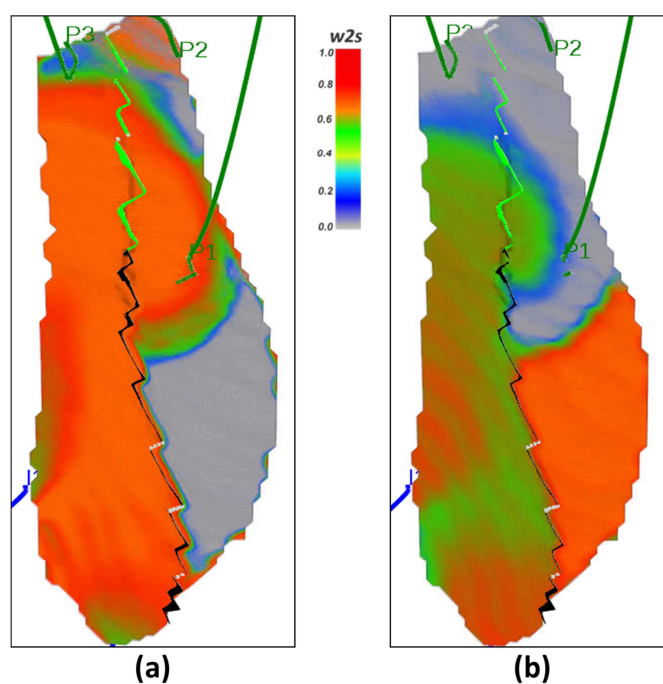


Figure 5. The observed well2seis attributes. (a) water-flooding well2seis attribute: obtained from correlating all the 4D seismic surveys to the field oil production history. (b) pressure well2seis attribute: obtained from correlating all the 4D seismic surveys to the field BHP behaviours.

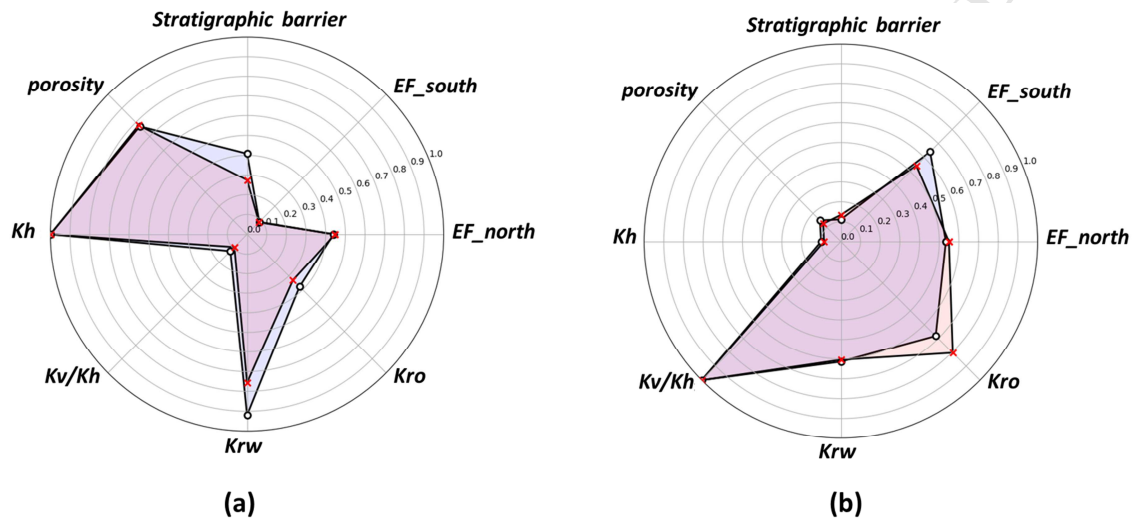


Figure 6. Results of the Morris sensitivity analysis. (a) Sensitivity analysis to water-flooding well2seis attributes. (b) Sensitivity analysis to pressure well2seis attributes. The black circle plots are for the average sensitivity μ , while the red-cross plots are for interactive effects σ .

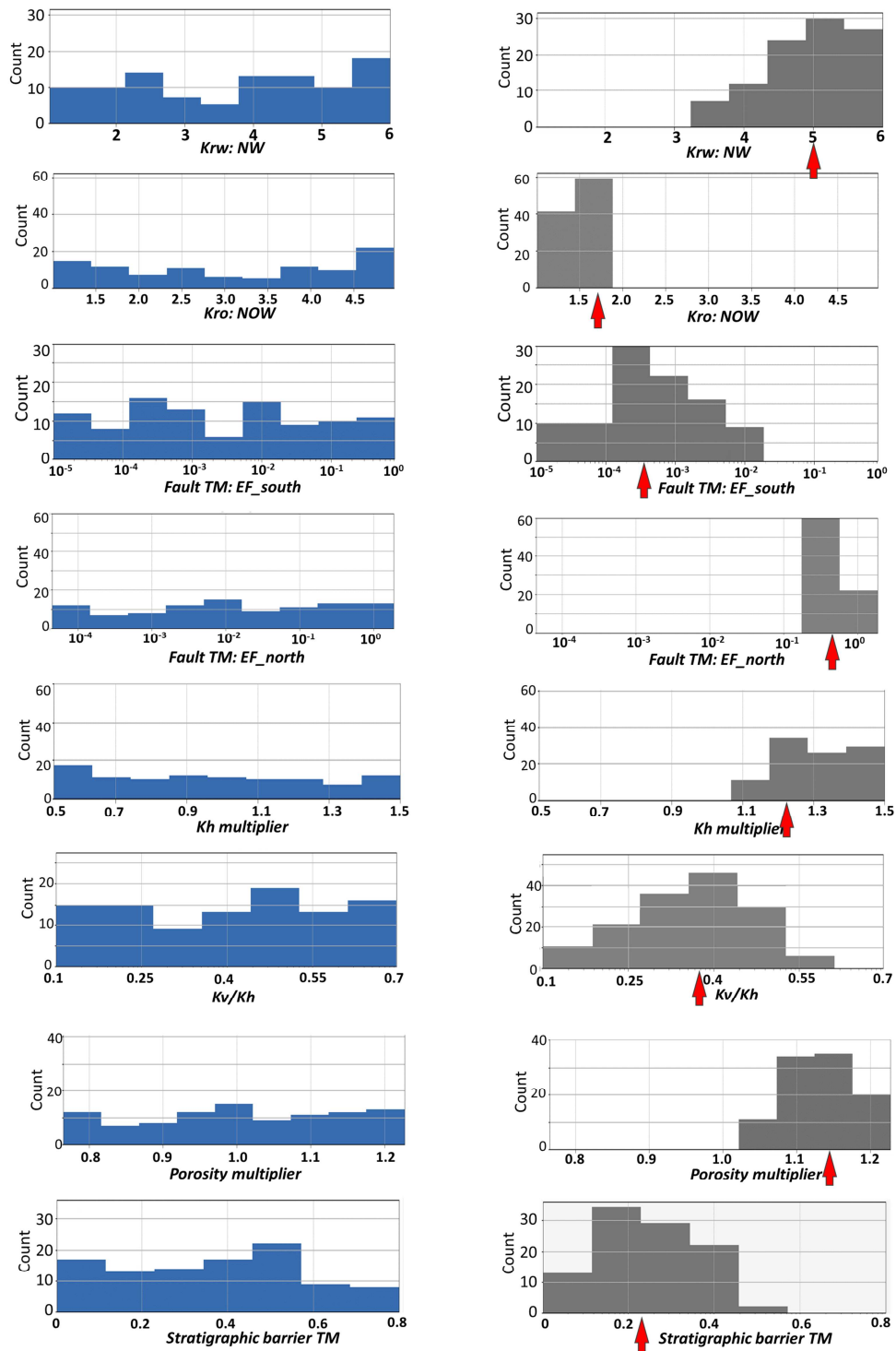


Figure 7. Left column: the distribution of the prior model parameters. Right column: the distribution of the posterior model parameters updated by the observed well2seis attribute after the third iteration. The red arrow indicates the value in the “True” case.

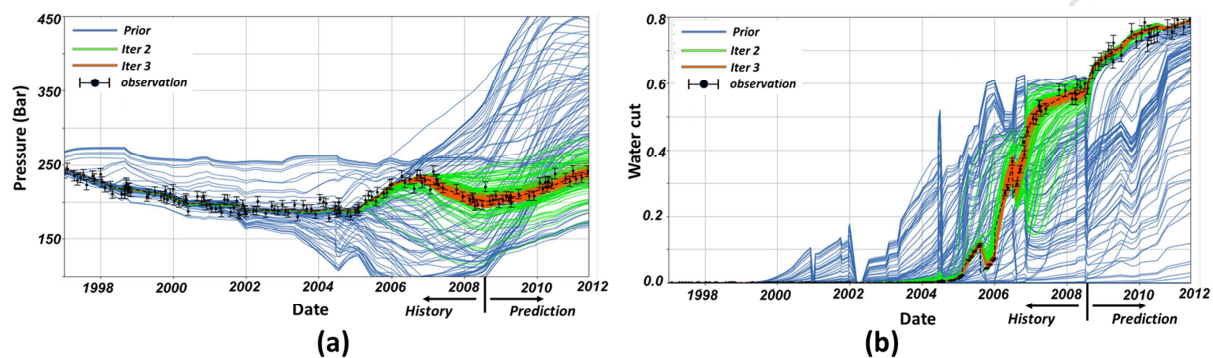


Figure 8. History matching results to the production data from the well2seis data assimilation: (a) average BHP of the three producers, (b) field water cut production.

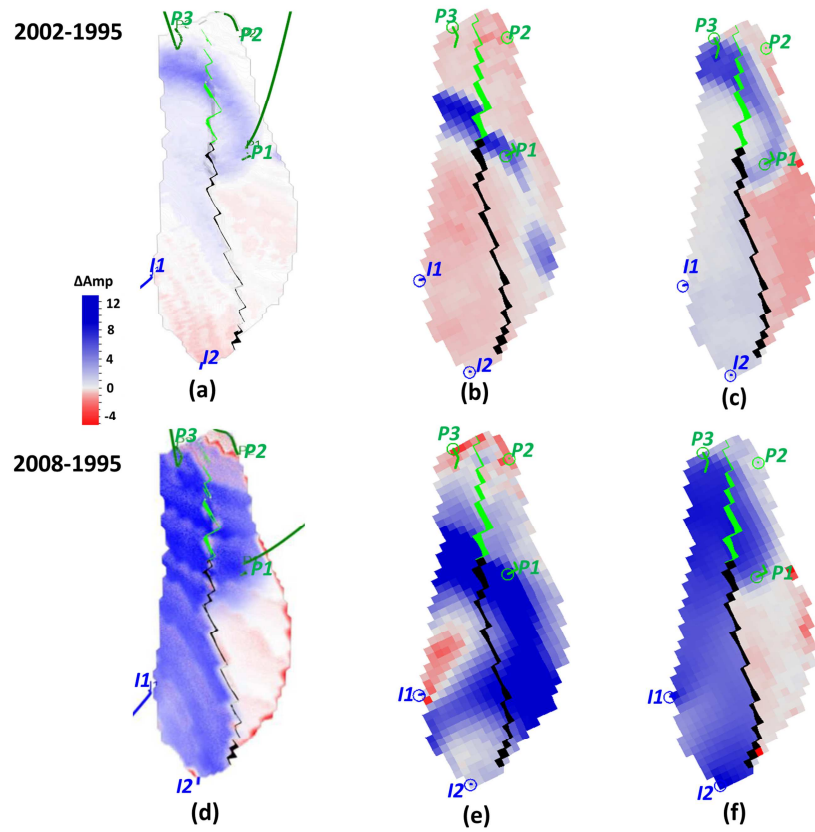


Figure 9 History matching results to the 4D seismic data from the well2seis data assimilation. The top row figures are for the 4D seismic difference between S3 (2002) and S1 (1995): (a) observed 4D seismic, (b) ensemble mean of the simulated 4D seismic difference from the prior ensemble models. (c) ensemble mean of the simulated 4D seismic from the posterior models after the third iteration. The bottom row figures are for the 4D seismic difference between S6 (2008) and S1 (1995): (d) observed 4D seismic, (e) ensemble mean of the simulated 4D seismic difference from the prior ensemble models. (f) ensemble mean of the simulated 4D seismic from the posterior models after the third iteration.

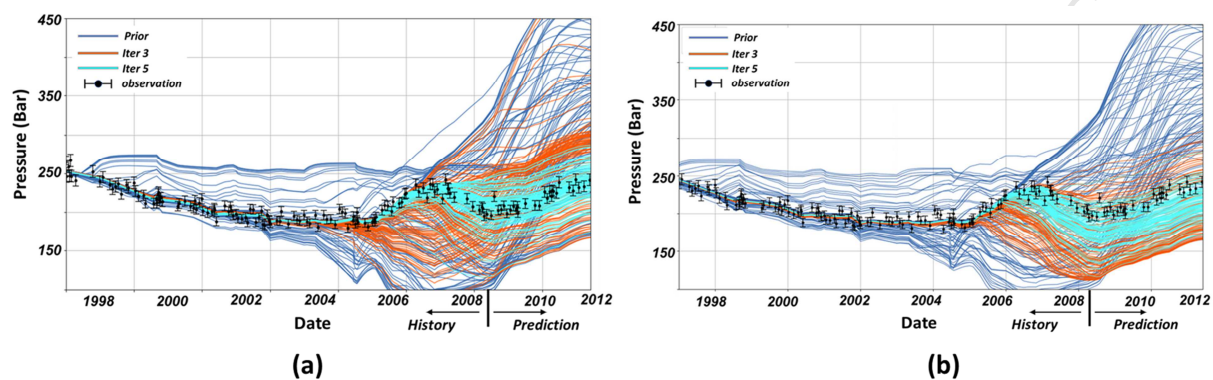


Figure 10. Matching quality to the production performance by: (a) data assimilation only using the production data; (b) data assimilation of 4D seismic data only.

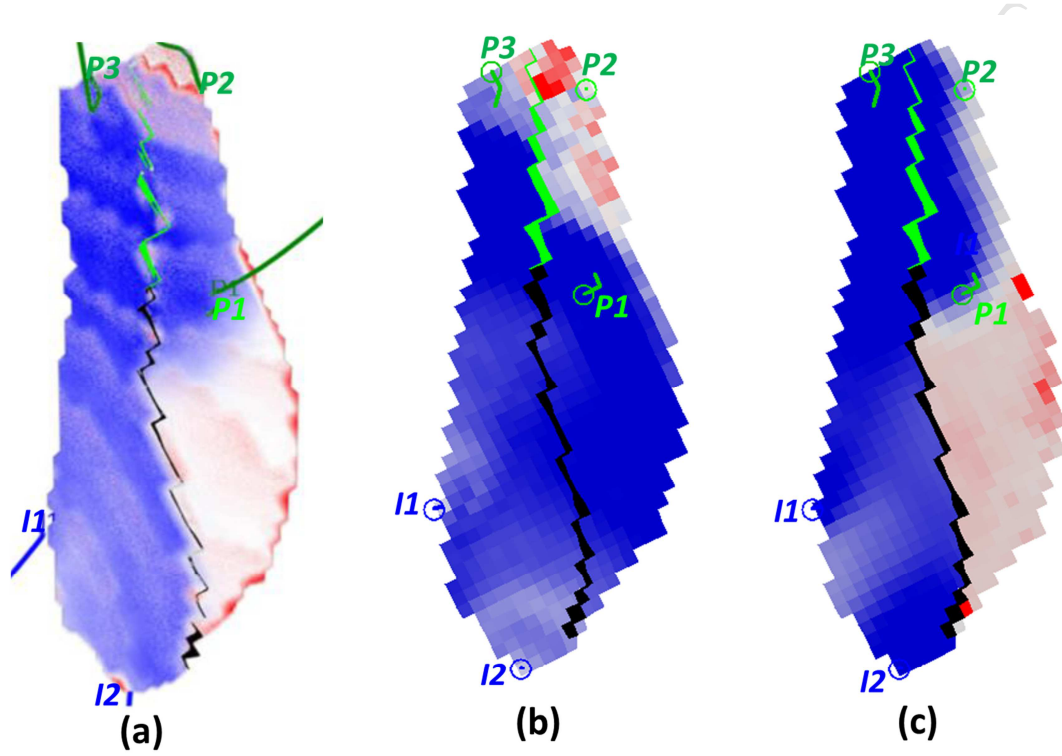


Figure 11. Comparison between observed and predicted 4D seismic attribute of S6 (2008)–S1 (1995): (a) observed 4D seismic data; (b) data assimilation using the production data only; (c) data assimilation using all the available 4D seismic maps from the six surveys.

8. Acknowledgments

We thank Equinor for sponsoring this research project. We also want to thank the sponsors of the Edinburgh Time Lapse Project Phase VI (AkerBP, BG, BP, CGG, Chevron, ConocoPhillip, ENI, Equinor, ExxonMobil, Halliburton, Hess, Science, Maersk, Nexen, Norsar, OMV, Petrobras, RSI, Shell, and Taqa) for supporting this research. The authors would like to specially thank Milana Ayzenberg, Rachares Petvipusit, Matteo Ravasi, Romain Chassagne, Hamed Amini and Mingyi Wong for the technical discussions, contributions and supports.

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10. Authorship Statement

First author: proposed the main workflow, conducted the technical development, drafted and revised this paper. Second author: provided critical insights by implementing the proposed workflow to real field assets, and assisted drafting of the manuscript. Third author: supervised the research project and provided critical insights in drafting and revising the manuscript.

Highlights

1. We developed and applied a new framework for assimilating frequently acquired 4D seismic data to update reservoir models.
2. The new method introduces a new attribute for seismic history matching.
3. This method **deploys** Morris sensitivity analysis and ES-MDA to analyse and calibrate uncertainty parameters in reservoir models.
4. The proposed framework **shows to boost** history matching efficiency when compared to the conventional history matching workflows.